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An inexact robust optimization method for supporting carbon dioxide emissions management in regional electric-power systems

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ABSTRACT

In this study, an inexact robust optimization method (IROM) is developed for supporting carbon dioxide (CO_2) emission management in a regional-scale energy system, through incorporating interval-parameter programming (IPP) within a robust optimization (RO) framework. In the modeling formulation, penalties are exercised with the recourse against any infeasibility, and robustness measures are introduced to examine the variability of the second-stage costs that are above the expected levels. The IROM is suitable for risk-aversive planners under high-variability conditions. The IROM is applied to a case of energy systems and CO_2 emission planning under uncertainty. The results obtained can generate desired decision alternatives that are able to not only enhance electricity-supply safety with a low system-failure risk level but also mitigate CO_2 emissions. They can be used for generating decision alternatives and minimizing the system cost of energy system while meeting the CO_2-emission permit requirement.

1. Introduction

With rapid economic development and continual urban expansion, energy demand is experiencing a sharply increase. Currently, many countries and regions are relying primarily on fossil-fueled resources (such as coal, oil and natural gas), such that 80% energy supply relies on fossil fuels around the world (Pekala et al., 2010). Carbon dioxide (CO_2) is a primary gas emitted from combustions of fossil fuels, and increasing CO_2 concentration is likely to lead to the increase in surface temperature, the change in global climate, and the rise in sea level. For example, approximately 38% of current CO_2 emissions can be attributed to the energy supply sector. The CO_2 concentration in the atmosphere have been increased from approximately 280 ppm in 1750 to 367 ppm in 1999, while the global CO_2 emissions are expected to exceed approximately 30 billion tons per year in the near future (Baede et al., 2001; Chen et al., 2010; Li et al., 2011). In addition, the average global temperature will rise in the range of 1.0 and 3.5 °C, and the sea-level will rise 15 cm to 95 cm in the next 90 years (Guo et al., 2012; Lean and Smyth, 2010). Many scientists are in puzzle about how to balance increasing electricity demands (due to population growth and economic development), less fossil fuel consumption, and mandated requirement for reducing CO_2 emission (Chen et al., 2010).

A great number of research efforts were undertaken for planning CO_2-emission mitigation in energy systems (Ang and Pandiyan, 1997; Fraser et al., 2013; Lin and Huang, 2010). For instance, renewable energy sources or less CO_2 intensive fuels were used, such as wind-power, natural gas power and nuclear power (CBC, 2003; Nasiri and Huang, 2008; Tampier, 2002). Carbon tax was proposed to encourage less carbon-intensive fuels and to exploit alternatives (Roughgarden and Schneider, 1999). Sequestration facilities were built up and used to capture CO_2 emitted from power plants during electricity generation process (NRC, 2006). Besides, CO_2-emission trading was envisaged within the Kyoto protocol as one of flexible mechanisms, which was introduced to help attain reduction of CO_2 emissions in a cost-effective way (Copeland and Taylor, 2000; Kemfert et al., 2004; Nahorski and Horabik, 2008; Su et al., 2010). Carlson and sholtz (1994) examined the impact of uncertainty on actual emission levels on the optimal design of trading schemes so as to limit price volatility. Ling (2006) proposed an interval stochastic two-stage linear programming model to consider how initial CO_2-emission permit should be allocated at the domestic and facility level with a politically and financially feasible allocation pattern. Chen et al. (2010) discussed CO_2-emission trading scheme with an integrated energy system using interval two-stage stochastic programming, which could deal with uncertainties expressed as discrete intervals and random variables. In general, two-stage stochastic programming (TSP) was effective for tackling optimization problems

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where an analysis of policy scenarios was desired and the model's coefficients were random with known probability distributions (Y.F. Li et al., 2010). However, a potential limitation of the conventional TSP is that it can only account for the expected second-stage cost without any consideration on the variability of the recourse values (Ahmed and Sahinidis, 1998). In TSP, the objective is to minimize the sum of the first-stage and expected second-stage costs, based on an assumption that the decision maker is risk neutral (Bai et al., 1997). As a result, the TSP may become infeasible when the decision maker is risk averse under high-variability conditions. However, due to complexities and uncertainties of energy systems, the desired energy resources allocation patterns may vary with time under high-variability conditions; this could result in energy systems becoming insecure and with a high risk of electricity shortage (and thus a high economic penalty). Security is a priority in energy systems planning throughout the world. Therefore, the conventional TSP has difficulties in emphasizing safety of energy system under high-variability conditions.

Robust optimization (RO) is an attractive technique that could help tackle the above shortcomings. RO can bring risk aversion into optimization models and find robust solutions to energy and environmental management problems. The concept of "robust" has two main implications: solution robustness and model robustness (Mulvey and Vanderbei, 1995). If the optimal solution obtained from a robust model remains "stable" when the input data has variations, it is regarded as solution robustness; if a solution deems "almost" feasible even if the input data has small change, it can be considered as model robustness (Fan and Huang, 2012; Watkins and Mckinney, 1997). In general, the conventional RO methods were effective in handling random variables when their probability distributions were available; however, the quality of available information about the uncertainties is often not satisfactory for establishing probability distributions. Moreover, even if the uncertainties expressed as probability distributions are available, it could be difficult to reflect them in large-scale stochastic models (Y.P. Li et al., 2010). In energy systems, various uncertain components may exist and may not be available as probability distribution, such as cost parameters, total electricity demand, residual capacities and capacity expansion limitations. Interval-parameter programming (IPP) is effective for handling uncertainties express as intervals. This requires that IPP be introduced into the RO framework to reflect the uncertainties with varied quality levels and presentation formats in energy systems.

Therefore, this study aims to develop an inexact robust optimization method (IROM) for planning CO_2-emission trading within an energy system. The IROM will incorporate interval-parameter programming (IPP) within robust optimization (RO) framework, such that uncertainties expressed as not only probability distributions but also interval values can be tackled. Moreover, penalties are exercised based on the recourse against any infeasibility and the consideration on the variability of the second-stage random costs. Therefore, IROM analyzes the results to gain insight into the tradeoff between energy system security and economic objective. A case study will then be provided for demonstrating the applicability of the developed method. Policy scenarios that are associated with different CO_2-emission mitigation levels will be analyzed. The detailed tasks include: (a) assigning power demand to different conversion technologies with a minimized system cost under uncertainty, (b) generating an optimized capacity-expansion scheme with considering timing and sizing, and (c) managing CO_2-emission with effective trading scheme.

2. Methodology

TSP can effectively handle uncertainties presented as probability distributions, leading to the loss of valuable information in many real-world planning problems. In TSP, decision variables are divided into two subsets: those that must be determined before the realizations of random variables are known, and those (recourse variables) that are determined after the realized random variables are available. A two-stage stochastic linear programming model can be formulated as follows (Li et al., 2006):

$$\text{Min} \quad f = C_{T_1}X + \sum_{h=1}^{s} p_h D_{T_2} Y \tag{1a}$$

subject to

$$A_r X \le B_r, r \in M, M = 1, 2, \ \ldots \ , m_1 \tag{1b}$$

$$A_i X + A_i^{'} Y \ge \tilde{w}_{ih}, i \in M; M = 1, 2, \ \ldots \ , m_2; h = 1, 2, \ \ldots \ , s \tag{1c}$$

$$x_j \ge 0, \ \ x_j \in X, j = 1, 2, \ \ldots \ , n_1 \tag{1d}$$

$$y_{jh} \ge 0, j_{jh} \in Y, j = 1, 2, \ \ldots \ , n_2; h = 1, 2, \ \ldots \ , s \tag{1e}$$

In the above model, $x_j^{\pm}$ and $y_{jh}^{\pm}$ represent the first- and second-stage decision variables, respectively; random variables take discrete values $\tilde{w}_{ih}$ with probability levels p_h, where h = 1, 2, … , s and $\sum p_h = 1$. Obviously, the TSP can effectively deal with uncertainties in the right-hand sides presented as random variables when the coefficients in the objective function and left-hand sides of constraints are deterministic.

Obviously, the TSP can tackle uncertainties expressed as random variables; moreover, it can also reflect economic penalties as corrective measures or recourse against any infeasibilities arising due to a particular realization of an uncertain event. However, it could neither account for the variability of the random second-stage cost nor capture the notion of risk under uncertainty (Bai et al., 1997). Fortunately, the robust optimization (RO) method can tackle these complexities. In fact, the RO method is a hybrid of stochastic and goal programs, to balance tradeoff between the expected recourse costs and the variability of these random values (Mulvey and Vanderbei, 1995). Consequently, through incorporating the RO approach within the above TSP framework, a stochastic RO model can be formulated as follows:

$$\text{Min } f = C_{T_1}X + \sum_{h=1}^{s} p_h D_{T_2} Y + \rho \sum_{h=1}^{s} p_h \left| D_{T_2} Y - p_h \sum_{h}^{s} D_{T_2} Y \right| \tag{2a}$$

subject to

$$A_r X \le B_r, r \in M; M = 1, 2, \ \ldots \ , m_1 \tag{2b}$$

$$A_i X + A_i^{'} Y \ge \tilde{w}_{ih}, i \in M; i = 1,2, \ \ldots \ ,m_2; h = 1,2, \ \ldots \ ,s \tag{2c}$$

$$x_j \ge 0, \ \ x_j \in X; \ \ j = 1, 2, \ \ldots \ ,n_1 \tag{2d}$$

$$y_{jh} \ge 0, \ \ x_j \in Y; \ \ j = 1, 2, \ \ldots \ ,n_2; h = 1, 2, \ \ldots \ ,v \tag{2e}$$

In the above modeling formulation, the term of $\left| D_{T_2} Y - \sum_{h}^{s} p_h D_{T_2} Y \right|$ is a variability measure on the second-stage penalty costs; the nonnegative factor ρ represents a weight coefficient. Depending on the value of ρ, the optimization may favor solutions with a higher expected second-stage cost $\sum_{h}^{s} p_h D_{T_2} Y$ in exchanging for a lower variability in the second-stage penalty costs as measured by $\left| D_{T_2} Y - \sum_{h}^{s} p_h D_{T_2} Y \right|$ (Takriti and Ahmed, 2004). When ρ = 0, the RO model can become a conventional TSP one; the objective is only to minimize the first-and second-stage costs. This also implies that the decision makers possess a risk-neutral attitude and would not consider the variability of the uncertain recourse costs. However, when ρ = 1, the decision makers can consider the variability of the second-stage cost based on a risk-